

Accepted Manuscript

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PII: S1350-4495(14)00042-5

DOI: <http://dx.doi.org/10.1016/j.infrared.2014.02.013>

Reference: INFPHY 1509

To appear in: *Infrared Physics & Technology*

Received Date: 31 December 2013

Please cite this article as: H. Jin, Y. Wang, A fusion method for visible and infrared images based on contrast pyramid with teaching learning based optimization, *Infrared Physics & Technology* (2014), doi: <http://dx.doi.org/10.1016/j.infrared.2014.02.013>

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A fusion method for visible and infrared images based on contrast pyramid with teaching learning based optimization

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Abstract

This paper proposes a novel image fusion scheme based on contrast pyramid (CP) with teaching learning based optimization (TLBO) for visible and infrared images under different spectrum of complicated scene. Firstly, CP decomposition is employed into every level of each original image. Then, we introduce TLBO to optimizing fusion coefficients, which will be changed under teaching phase and learner phase of TLBO, so that the weighted coefficients can be automatically adjusted according to fitness function, namely the evaluation standards of image quality. At last, obtain fusion results by the inverse transformation of CP. Compared with existing methods, experimental results show that our method is effective and the fused images are more suitable for further human visual or machine perception.

Keywords: image fusion, TLBO, contrast pyramid, optimization

1. Introduction

The spectrum is divided into IR, visible and UV spectroscopy, which have their own principles and characteristics of imaging, in different wavelength regions. In practical applications, multispectral resolution and high spatial resolution images are more widely used. Thus, the visible and infrared image fusion has become a hot topic in the field of image fusion. It is hoped that through some kind of image fusion techniques to fully complement both information, and access to more detail and accurate information on the scene, it is possible to locate the position of the heat source for identifying camouflage, testing resources, night vision and so on.

Image fusion refers to a multichannel source image data acquired on the same object after the image processing and computer technology, enabling to maximally extract the favorable information of each channel, and finally integrated into a high-quality image, the purpose is to improve the utilization of image information, the accuracy and reliability of the computer interprets and the spatial resolution and spectral resolution of the original image, which will help to monitor. This paper relates to the visible and infrared images fusion with having a wide range of practical value in many areas, such as electronics testing, military combat, lunar exploration, medical image analysis and so on.

Nowadays, there are already a lot of methods in the field of images fusion. For example, the intensity-hue-saturation (IHS) transposition,¹ principal component analysis (PCA),² Brovey algorithm,³ wavelet-based methods,^{4,5,6,7} or various pyramid algorithms such as contrast pyramid^{8,9,10,11}, etc. They are relatively simple image fusion method and most widely used, but there are still various deficiencies. For instance, the former three fusion methods can lead to different degrees of spectral distortion and lower spatial resolution. The wavelet-based fusion

methods may generate “ringing” effects. CP-based fusion method can obtain better results, but its fusion coefficients are set by experience and are constants, there is very great blindness. We put forward a new method that TLBO^{12,13,14} approaches to maximally optimize fusion coefficients on the basis of CP decomposition, changing the previous pattern of fixed coefficients selection, to achieve superior fusion effect.

The rest of the paper is organized as follows. In Section 2, the decomposition and reconstruction of CP is briefly reviewed, and TLBO is simply introduced in Section 3. Then the application of TLBO for optimizing coefficients is described in detail in Section 4, Section 5 explains the principle and fitness function of the proposed method. The effect images and analysis of experiments are showed in Section 6. Finally, the conclusion is summarized in Section 7.

2. Decomposition and reconstruction of CP

The pyramid of an image is calculated from bottom to top. It is decomposed each image into pyramid image sequence of multiple scales, high resolution image in the lower layer, low resolution image in the upper, the size of the upper image is a quarter of previous layer image'. In consideration of CP derived from Gaussian pyramid, every level of which is formed by the previous one through filtering, we first build the Gaussian window function. Suppose w denote 5×5 window function, and satisfy the following constraints:

(1) Separability

$$w(m, n) = w(m)w(n), m \in [-2, 2], n \in [-2, 2] \quad (1)$$

(2) Normalized

$$\sum_{m=-2}^2 w(m) = 1 \quad (2)$$

(3) Symmetry

$$w(m) = w(-m) \quad (3)$$

(4) Parity items such as contribution

$$w(-2) + w(2) + w(0) = w(-1) + w(1) \quad (4)$$

These constraints are used to ensure the performance of the low-pass, and the brightness of images is smoothness after shrinking and expanding, it does not appear the joint effect. We can construct: $w(0)=3/8$, $w(1)=w(-1)=1/4$, $w(2)=w(-2)=1/16$, the window function can be mathematically expressed as:

$$w = \frac{1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix} \quad (5)$$

Gaussian pyramid as a set of image sequence, each level are made at the next higher level image through a low-pass filter and the down-sampling process. The frequency band of two adjacent is reduced by $1/8$ rate, the image size by $1/4$ rate decreases. Here we set the source image

is $G_0(i, j)$, $i \leq M^0$, $j \leq N^0$, that is Gaussian pyramid's bottom image, M^0 , N^0 is the number of columns and rows of the image respectively. G_l represents the first l -level of Gaussian pyramid, $0 < l \leq N$ (N is the total number of layers). To get G_l , it must firstly take G_{l-1} and the above constructed window function w convolve, and then the convolution result is done the down-sampling in interlaced columns and rows. Computation formulation is as follows.

$$G_l = \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) G_{l-1}(2i+m, 2j+n), 0 < l \leq N, 0 \leq i < u, 0 \leq j < v \quad (6)$$

where u, v , denote the number of columns and rows of the first l layer pyramid image, respectively; w is namely the above defined 5×5 low-pass filter.

After winning Gaussian pyramid, it will be interpolated to enlarge. We introduce enlarge operator, that is interpolate new samples between the given numerical by using interpolation method. A certain level of the pyramid image is extended into the size of the former level image. Thus, it can solve the problem of these levels' different in sample density. If carry out the following operation on G_l , we can get the new image owning the same size as G_{l-1} .

$$G_{l-1}^*(i, j) = 4 \sum_{m=-2}^2 \sum_{n=-2}^2 w(m, n) G_l\left(\frac{i+m}{2}, \frac{j+n}{2}\right), 0 < l \leq N, 0 \leq i < u, 0 \leq j < v \quad (7)$$

where $G_l\left(\frac{i+m}{2}, \frac{j+n}{2}\right) = \begin{cases} G_l\left(\frac{i+m}{2}, \frac{j+n}{2}\right) & \text{where } (i+m/2, j+n/2) \text{ is integer coordinates} \\ 0 & \text{otherwise} \end{cases}$

Every level of CP C_l , is a ratio of the corresponding Gaussian image at all levels. It is defined as

$$\left. \begin{aligned} C_l &= G_l / G_l^*, & 0 \leq l \leq N-1 \\ C_N &= G_N, & l = N \end{aligned} \right\} \quad (8)$$

Than we consider CP reconstruction, which is the inverse process of decomposition. According to the iteration of formulation (8), set $l = N, N-1, \dots, 0$, starting from the top of CP and turning down, we can get each layer of Gaussian pyramid: $G_n, G_{n-1}, \dots, G_0$. The reconstruction image G_0 is the final fusion image. The formulation is as follows.

$$\left. \begin{aligned} G_N &= C_N, & l = N \\ G_l &= C_l G_l^*, & 0 \leq l < N \end{aligned} \right\} \quad (9)$$

where G_l^* is the same size as G_l after G_{l+1} interpolated.

The original images are decomposed as a series of decomposition layers, which have different resolutions and spatial frequency, by the multiscale CP decomposition. At the same time, each of the decomposition levels reflects the contrast information of the corresponding spatial frequency. The fusion process is conducted in every spatial frequency layer respectively, so it may be aimed at the features and details of different frequency bands on different decomposition levels by using different fusion operators, for the purpose of highlight the features and details of the specific frequency band. It follows the principle that the human retinal image is processed in different frequency channel, so it may gain the fusion effect which is more close to the human visual characteristics. Through many literatures and simulation experiments, CP fusion method is better than general pyramidal decomposition and wavelet transform for visible and infrared images fusion. However, there are inherent weaknesses: the selection of weighted coefficients is mostly

based on experience, which is the coefficients values are prior set, it can be easy to cause unstable fusion effect. To improve this situation, we adopt the heuristic evolutionary algorithm, TLBO, which can search and estimate the fusion coefficient in certain decision space, adaptively modify weighted coefficients, in order to achieve the optimization of the fusion effect.

3. Teaching learning based optimization

TLBO introduced by Rao et al,^{15,16,17} is novel mathematical model prepared and implemented for the optimization of a unconstrained non-linear continuous function, and is also a new variant of meta-heuristic optimization technique inspired by the natural phenomenon of teaching and learning process. Meanwhile, liking other nature-inspired algorithms, TLBO is also a population-based method that uses a population of solutions to proceed to the global solution. Assume one class C , which own the same merit level learners and is tough by the two different quality of teachers T_1 and T_2 , obtains mean value M_1 and M_2 , respectively. We define that the marks distribution curve of the class is a normal distribution, as formulation (10), in spite of having certain deviation with the actual, it still be help for analysis. We can draw as Fig.1 that describes the above definition.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad (10)$$

where μ is the mean, σ^2 is the variance and x is any value in certain range.

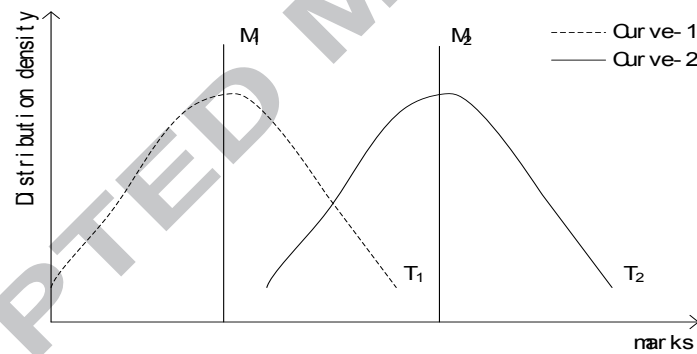


Fig.1 Model for the distribution of marks for two groups

Fig.1 shows the two curves, one dotted line Curve-1 and the other solid line Curve-2, respectively represent the relation of between distribution density and marks under the two different teachers teaching T_1 and T_2 . The approximately middle vertical virgule corresponding abscissa values are mean value M_1 and M_2 . The terminal corresponding abscissa value of curves represents the best mark in the class, which is also the ability of teachers. The teacher own the most knowledgeable in the society, he or she will impart knowledge to every learner in this class, so that learners' marks will be improved, the higher marks the learners obtain, the higher the mean values are. However, it must be noted that no matter how the teachers do their best effort, the mean is unlikely to be the level of the teacher in terms of knowledge. In order to improve the mean value, it requires a new teacher of superior quality. Furthermore, the learners can also learn from each other. So TLBO is composed by two basic operation, namely teaching phase and learner phase, teaching phase means learning from the teacher and learner phase means learning through the interaction between learners. Brief descriptions of the two phases are given as follows.

3.1 Teaching phase

The mean value improvement of a class mainly relies on a good teacher, so selecting a knowledgeable teacher is a key of acquiring a good result. The teaching phase is also primarily responsible for the global search property of TLBO algorithm. In reality, most individuals hope the every learner's mark always rises by acquiring supreme knowledge from the most knowledgeable person. Whereas it is not possible because of the random of the process, the teacher can only boost the average grade of a class to some extent. Suppose $X_{old,i}$, $X_{new,i}$, respectively denote the previous mark of learner X and his or her new mark through learning from a teacher at the i th iteration. How motivate $X_{old,i}$ to $X_{new,i}$ depends on the difference between the existing and the new mean value, let M_i be the existing mean value and $M_{new,i}$ be the new mean value, Therefore the new solution is defined according to the following expression:

$$X_{new,i} = X_{old,i} + r_i (M_{new,i} - T_F M_i) \quad (11)$$

where r_i is a random number, and $r_i \in [0,1]$, T_F is a teaching factor that decides how the mean value to be changed. Because T_F is either 1 or 2, it can be designed as follows:

$$T_F = \text{round}[1 + \text{rand}(0,1)] \quad (12)$$

3.2 Learner phase

The learner phase of TLBO algorithm is that learners enhance their knowledge by interaction, which also is help for improving the mean value. Every learner obtains new things from another learner randomly selected, when the selected one has more knowledge than him. So it is indispensable to judge the pros and cons of both before interaction. Where let X_i be one learner, X_j be another which is different from the former. By using the concept of learner phase, the improvement of the grade point of learners may be represented as follows:

```

for i=1:N
if f(Xi) > f(Xj)
Xnew,i = Xold,i + ri (Xi - Xj)
else
Xnew,i = Xold,i + ri (Xj - Xi)
endif
endfor

```

where N is the number of iteration, r_i is a random number, and $r_i \in [0,1]$, fitness function $f(X)$, and define the optimization problem as: maximize $f(X)$, accept $X_{new,i}$ if it gives a better value.

4. The application of TLBO algorithm for optimizing coefficients

In this section, the application of TLBO will be particularly described. The whole process is showed as follow the flowchart, Fig.2.

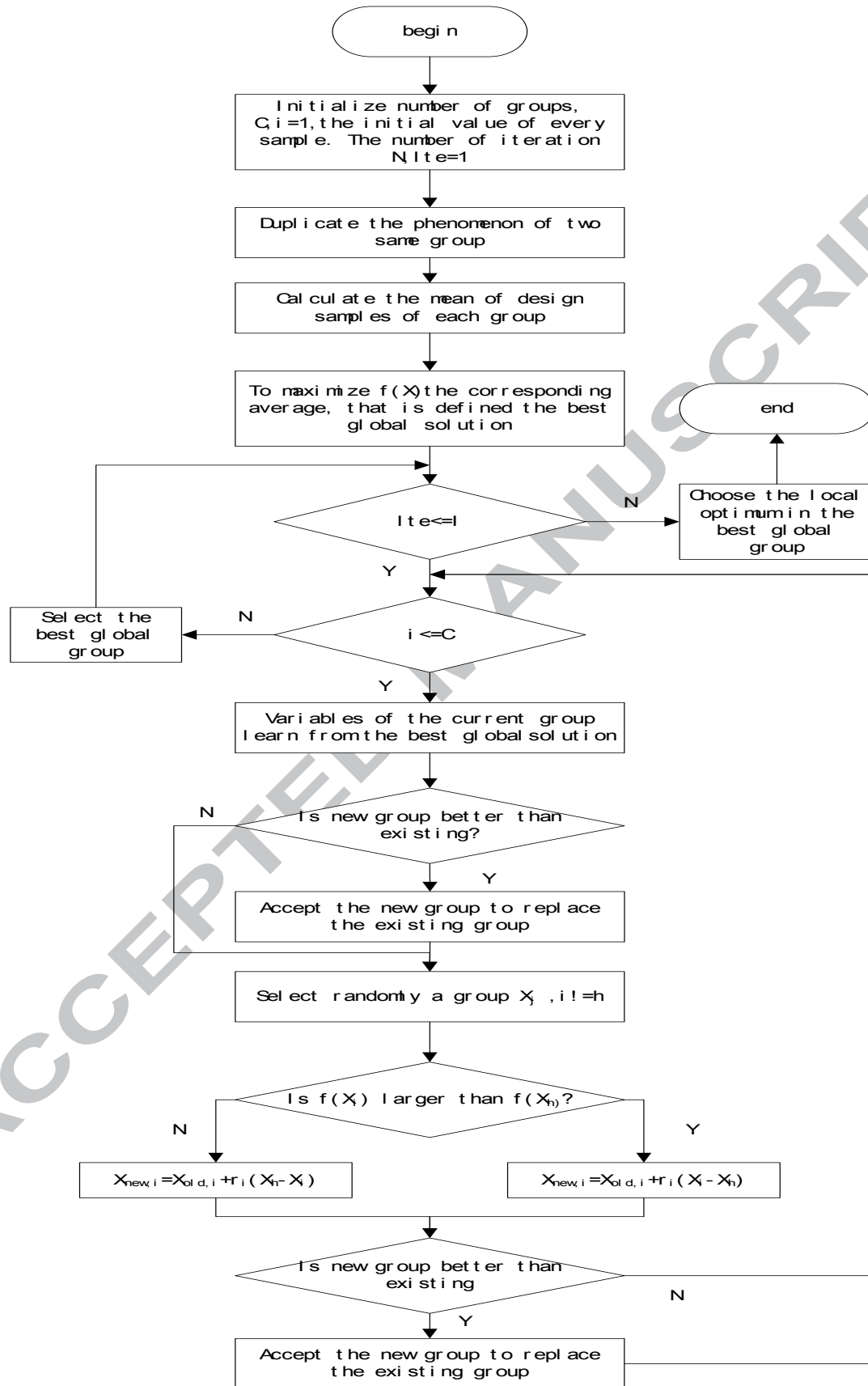


Fig.2 Flowchart for TLBO optimizing coefficients

According to the flowchart, the procedure of TLBO optimizing coefficient is briefly explained

at the following steps.

Step 1: Define the optimization coefficients and initialize the optimization group, the number of iteration.

Firstly, giving a range (depending on the practical situation) of the coefficients, set up the value of samples in this range, randomly, and the samples are divided into the same size group. All of samples are called *population*,

$$population = \begin{bmatrix} X_{1,1} & X_{2,1} & \dots & X_{G,1} \\ X_{1,2} & X_{2,2} & \dots & X_{G,2} \\ \dots & \dots & \dots & \dots \\ X_{1,S} & X_{2,S} & \dots & X_{G,S} \end{bmatrix} \quad (13)$$

where define $X_{i,j}$ as the value of the first j sample of the first i group, $1 \leq i \leq G$, $1 \leq j \leq S$, and i, j are integers. At the same time, let the number of the iteration as I , and the subscript of I is *ite*, initialize *ite* = 1.

Step 2: Deal with data of group, define fitness function: maximize $f(X)$.

Need to calculate mean value of every group M_i . Then pick out the optimal average group X_T according to the fitness function, which will act as the teacher.

Step 3: Teaching phase

Let all samples of every group except the teacher learns from M_T . Here there is a nested loop, express as follows:

```
for i=1:G
for j=1: S
if i ≠ T
 $X_{new, i, j} = X_{old, i, j} + r_i (X_{Tj} - T_F M_i)$ 
endif
endfor
endfor
```

then, judge whether the new solution is better than the existing or not, and decide to refuse or accept.

Step 4: learner phase

Under the first loop of the step-3, randomly choose X_h from groups, and $i \neq h$, begin to learn from interaction.

```
if  $f(M_i) < f(M_h)$ 
for j=1: S
 $X_{new, i, j} = X_{old, i, j} + r_i (X_{ij} - X_{hj})$ 
endfor
else
for j=1: S
 $X_{new, i, j} = X_{old, i, j} + r_i (X_{hj} - X_{ij})$ 
endfor
endif
```

Accept the new group if it gives better results, and execute step-3 and step-4 until the end of the first loop. It needs to pick out the best group again and go to step-2.

Step 5: Finding out the final best result

Repeat step-2~step4 until $ite = I$. At the time of iteration termination, find out the local optimal sample from the best group.

By the above steps, we can draw a conclusion that the application principle of TLBO to optimize coefficients is from global to local. Firstly, choose the optimal group, and then the optimal sample will be selected from the specific group. The selection strategy is very critical, not only decide the location of the optimal coefficients, but also accurate the final result. However, there are still some problem with worth of our attention, for instance: the number of samples and groups, it must be appropriate, if having too many samples of a group, it can lead to the slowly moving of global average, otherwise, it can occur that the selection of local is inadequacy. In addition, more groups can cause unnecessary waste of time and less can't reach the deal solution.

5. Image fusion algorithm based on CP with TLBO

In this section, we explain how to fuse visible and infrared image based on contrast pyramid with TLBO (TLBO-CP), and set fitness function that evaluation the quality of fusion images.

5.1 Principle of fusion based on CP with TLBO

Let $MG1$ and $MG2$ be the visible image and the infrared images, respectively. They have the same size $N \times N$ as the original input images. And initialize the number of CP decomposition levels is l . Through the procedure of CP decomposition, the original images become the two images, $CPM1$ and $CPM2$ simultaneously with the same size $(N/2^l) \times (N/2^l)$. The couple of images will wait for fusion until the optimal coefficients are chosen by TLBO according to the fitness function. Start iteration after initializing all basic variable, the detailed process of iteration has already been expressed at the Step-2~Step-4 of the section 4. Assume the optimal coefficients k_1 , k_2 . The CP decomposition images can carry out fusion. Formulation is as follows:

$$CP_Fus = CPM1 \times k_1 + CPM2 \times k_2 \quad (14)$$

5.2 Fitness function for assessing the quality of fusion images

In order to better estimate image sharpness, we usually select more than one measure methods. Here are three measure techniques which are employed to as fitness function in this experiment, as follows:

(1) Information Entropy (IE), is a concept of quantitative information, and the larger the value is, the more the image information is. Its corresponding mathematic expressions are also given as follows.

$$H = - \sum_{i=0}^{L-1} p_i \log p_i \quad (15)$$

where H denotes IE of the image, L is the total gray level of the image, p_i denotes the ratio of the pixel number N_i of the gray value i and the total pixel number N , namely

$$p_i = N_i / N \quad (16)$$

(2) Average Grads (AG), can sensitively react the presentation skills of image to tiny detail, and appraise the image sharpness. Here $\bar{g}$ denotes AG, and can be mathematically expressed as

$$\bar{g} = \frac{1}{(M-1)(N-1)} \times \sum_{i=1}^{(M-1)} \sum_{j=1}^{(N-1)} \sqrt{\left(\frac{\partial f(x_i, y_j)}{\partial x_i} \right)^2 + \left(\frac{\partial f(x_i, y_j)}{\partial y_j} \right)^2} / 2 \quad (17)$$

where $f(x,y)$ is the image function, M and N are the rows and columns of the image, respectively.

(3) Standard Deviation (SD), is an important index measure of image information richness, beyond that it can evaluate image contrast size. Its computation formulation is as follows.

$$S_{td} = \left(\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^{\frac{1}{2}} \quad (18)$$

where S_{td} denotes SD, $\bar{x}$ is the mean value of the image pixel and x_i is the pixel value of the image.

6. Numerical experiments

In the experiments, we firstly choose a couple of visible and infrared images of night scene as Fig.3 (a) and (b), they are used be 256×256 pixels and the gray-scale map. The other two groups of images have the same size as the first one and are colorized. Fig.4 (a) and (b) are the visible light image with band 1 (0.45 to 0.52 μm) and the infrared thermal image respectively, of satellite images of Copenhagen City, Denmark. They were acquired on 26 May 1992. The last pair were respectively captured with a Sony Camcorder and a LWIR sensor, and showed that men and building with (Fig.5 (a)) and without (Fig.5 (b)) a smoke screen in cloudy weather.

In this paper, we employ the PCA-based fusion method, wavelet-based fusion method and CP-based fusion method to compare with TLBO-CP method proposed. The number of decomposition levels of wavelet and CP transform is both three and the principle of their fusion also choose larger value. In the process of optimizing coefficients, the samples' values of population are initialized between 0 and 1.



(a)



(b)



(c)



(d)



(e)



(f)

Fig.3 (a)Original visual light image (b)Original infrared thermal image (c)PCA-based fusion result (d)Wavelet-based fusion result (e)CP-based fusion result (f)TLBO-CP fusion result



(a)



(b)



(c)



(d)



(e)

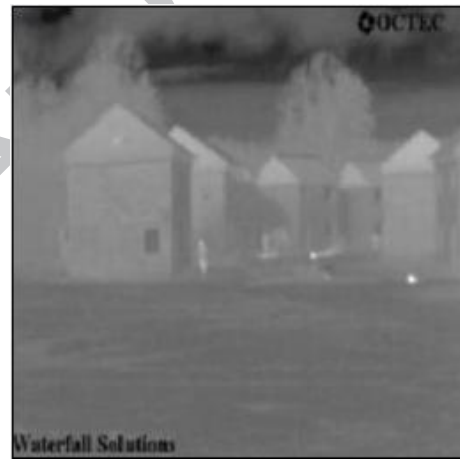


(f)

Fig.4 (a)Original visual light image (b)Original infrared thermal image (c)PCA-based fusion result (d)Wavelet-based fusion result (e)CP-based fusion result (f)TLBO-CP fusion result



(a)



(b)



(c)



(d)



Fig.5 (a)Original visual light image (b)Original infrared thermal image (c)PCA-based fusion result (d)Wavelet-based fusion result (e)CP-based fusion result (f)TLBO-CP fusion result (Color online only)

6.1 Visual analysis

The experimental results have been showed from Fig.3 to Fig.5. We can clearly find Fig.3 (c), Fig.4 (c) and Fig.5 (c) with seriously spectral information loss, which are based on PCA method fusion, especially Fig.5 (c), basically don't see the target object. Then the Wavelet-based fusion images well display the visual effect of fusing visible and infrared images. But it is not hard to see details of the rough and faint hue from (d) of Fig.3~Fig.5. The last two images of every group respectively based CP fusion and TLBO-CP fusion have better fusion result. Comparing the fusion effect of the two methods, we can find that fusion results based TLBO-CP have higher intensity, better fuse the characteristics and details of the two original images, express more rich information level of fusion image, and highlight the objects, which will be more conducive to analysis in practical application.

6.2 Quantitative analysis

In order to evaluate objectively those methods mentioned above, we list the calculation results of fitness function described in section 5.2, as follows Table1~Table3, corresponding to Fig.3~Fig.5. Although the numerical results of each experimental of TLBO-CP is unequal for randomness, it has been fluctuating in a small region. From the data of IE, AG, STD, IE value of the new method proposed is litter higher than the former even lower, but the values' promotion of AG and STD are absolute superiority, which shows that images based TLBO-CP fusion have higher resolution and more abundant information, not only reflect the detail features, but also retain spectral information better. So our method also has better objective evaluation criteria. However, it is a problem to be introduced that run time is higher, because of the higher algorithm complexity of TLBO-CP. Suppose the number of iterations is I , the number of groups is G , and the number of samples of every group is S . So the number of the global coefficients selection becomes $2 \times I \times G$, and produce the same number of CP reconstruction and fitness function calculation, with producing $2 \times I \times G \times S$ coefficients. Finally, there is still a local coefficients selection requiring the $S+1$ times of CP reconstruction and fitness function calculation.

Table 1 Numerical results of Fig.3

Images	IE	AG	STD	Run time
Visual light color image	3.4236	2.856	27.1248	—
Infrared thermal image	4.6603	4.8559	32.8665	—
PCA-based fusion result	4.8325	5.9438	39.9533	0.2500
Wavelet-based fusion result	4.5077	6.0738	32.268	0.0940
CP-based fusion result	4.3297	6.7942	37.1387	0.0470
TLBO-CP fusion result	4.6996	9.9983	53.0902	11.6719

Table 2 Numerical results of Fig.4

Images	IE	AG	STD	Run time
Visual light color image	5.3444	17.8197	63.7882	—
Infrared thermal image	4.4731	6.5195	68.5229	—
PCA-based fusion result	5.1868	10.7996	62.9817	0.7960
Wavelet-based fusion result	5.2271	18.51	70.7156	0.3440
CP-based fusion result	5.1229	23.3201	81.2657	0.1570
TLBO-CP fusion result	4.4306	27.8164	95.9599	11.4069

Table 3 Numerical results of Fig.5

Images	IE	AG	STD	Run time
Visual light color image	4.9224	1.759	52.9171	—
Infrared thermal image	4.4127	1.7589	24.262	—
PCA-based fusion result	4.9454	1.7813	53.6764	0.0150
Wavelet-based fusion result	4.4394	2.3379	30.185	0.1090
CP-based fusion result	4.5823	2.6309	32.2092	0.1090
TLBO-CP fusion result	4.8984	2.725	48.7981	11.3909

7. Conclusion

This paper presents a novel scheme of the visible and infrared images fusion, TLBO-CP. This is employing the nature-inspired optimization algorithm of TLBO to self-adaptively choose the fusion coefficients by fitness function evaluation. And through a lot of experiments verify the method excels the previous methods in both visual effect and objective evaluation criteria. In addition, it is feasible and simple to implement in comparison with existing efficient methods in practical applications. Because of the capability of real-time low, it is better to carry out the new fusion method on the system without requiring real-time.

Acknowledgment

This work has been partially supported by the National Natural Science Foundation of China under grant No.61201416, 61303122. Also thanks to Octec limited for supplying the original images in the experiments.

References

1. T. M. Tu, S. C. Su, H. C. Shyu, and P. S. Huang, "Efficient intensity-hue-saturation-based image fusion with saturation compensation," *Opt. Eng.* 40(5), 720-728(2001).
2. G. Turhan-Sayan, "Real time electromagnetic target classification using a novel feature extraction technique with PCA-based fusion," *IEEE Trans. Antennas Propag.* 53(2), 766-776(2005).
3. Y. Y. Su, Y.J. Li, Z. F. Zhou, "Remote sensing image fusion methods and their quality evaluation," *Geotechnical Investigation&Surveying.* 40(12), 70-74(2012).
4. T. Pu and G. L. Ni, "Contrast -based image fusion using the discrete wavelet transform," *Opt. Eng.* 39(8), 2075-2082(2000).
5. J. Xiaoyu, G. Zhiyun, and Z. Liwei, "Multispectral image fusion using wavelet transform," *Acta Electron. Sin.* 25(8), 105-108(1997).
6. A. Cohen, I. Daubechies, and J. C. Feauveau, "Biothogonal base of compactly supported wavelets," *Commun. Pure Appl. Math.* 45(5), 485-560(1992).
7. H. H. Wang, J. X. Peng, and W. Wu, "Remote sensing image fusion using wavelet packet transform," *J. Image Graph.* 7(9), 932-936(2002).
8. A. Toet, "Hierarchical image fusion," *Mach. Vision Appl.* 3(1),1-11(1990).
9. A. Toet, "Multiscale contrast enhancement with application to image fusion," *Opt. Eng.* 31(5), 1026-1031(1992).
10. Ancuti. Co, Ancuti. c, "Single image dehazing by multi-scale fusion," *IEEE Trans. Antennas Propag.* 22(8), 3271-3282(2013).
11. H. Y. Jin, L.C. Jiao, "Fusion of infrared and visual images based on contrast pyramid directional filter banks using clonal selection optimizing," *Optical Engineering.* 47(2), 027002(2008).
12. B. Mandal, P. K. Roy, "Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization," *INTERNATIONAL JOURNANL OF ELECTRICAL POWER & ENERGY SYSTEMS.* 53, 123-134(2013).
13. V. Togan, "Design of planar steel frames using Teaching-Learning Based Optimization," *ENGINEERING STRUCTURES.* 34, 225-232(2012).
14. S. C. Satapathy, A. Naik, "Data clustering based on teaching-learning-based optimization," *SWARM, EVOLUTIONARY, AND MEMETIC COMPUTING, PT.* 7077, 148-156(2011).
15. R. V. Rao, V. J. Savsani, D. P. Vakharia, "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems," *Computer-Aided Design.* 43, 303-315(2011).
16. R.V. Rao, V.J. Savsani, "Teaching-learning-based optimization algorithm for unconstrained and constrained real-parameter optimization problems," *ENGINEERING OPTIMIZATION.* 44(12), 1447-1462(2012).
17. R. V. Rao, V. J. Savsani, Vakharia.DP, "Teaching-learning-based optimization: An optimization method for continuous non-linear large scale problems," *INFORMATION SCIENCE.* 183(1), 1-15(2012).

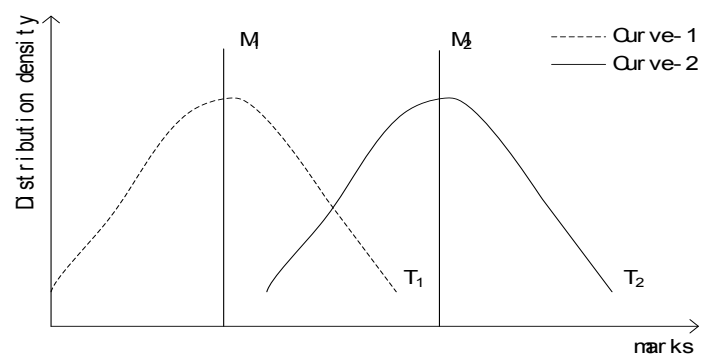


Fig.1 Model for the distribution of marks for two groups

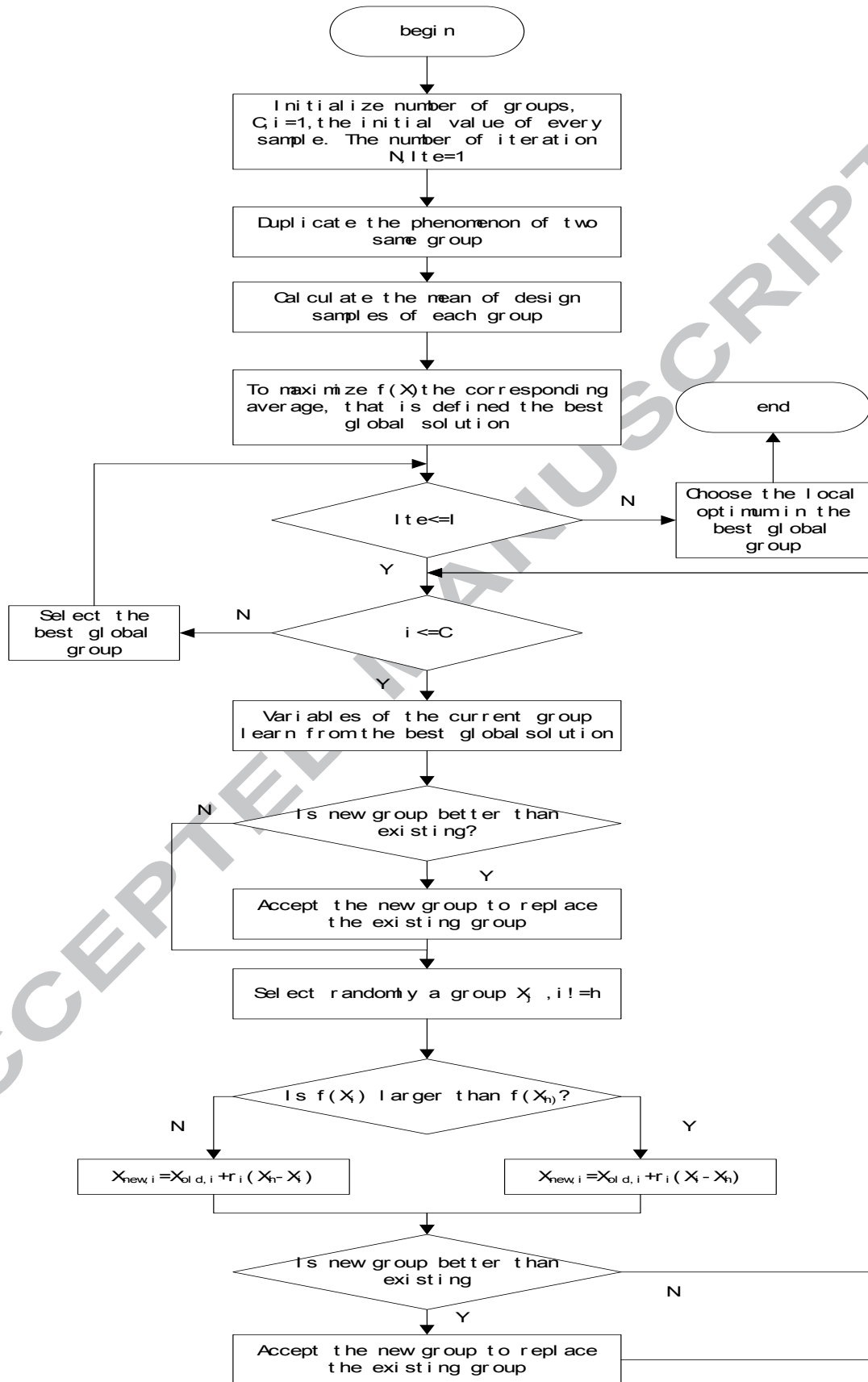


Fig.2 Flowchart for TLBO optimizing coefficients



























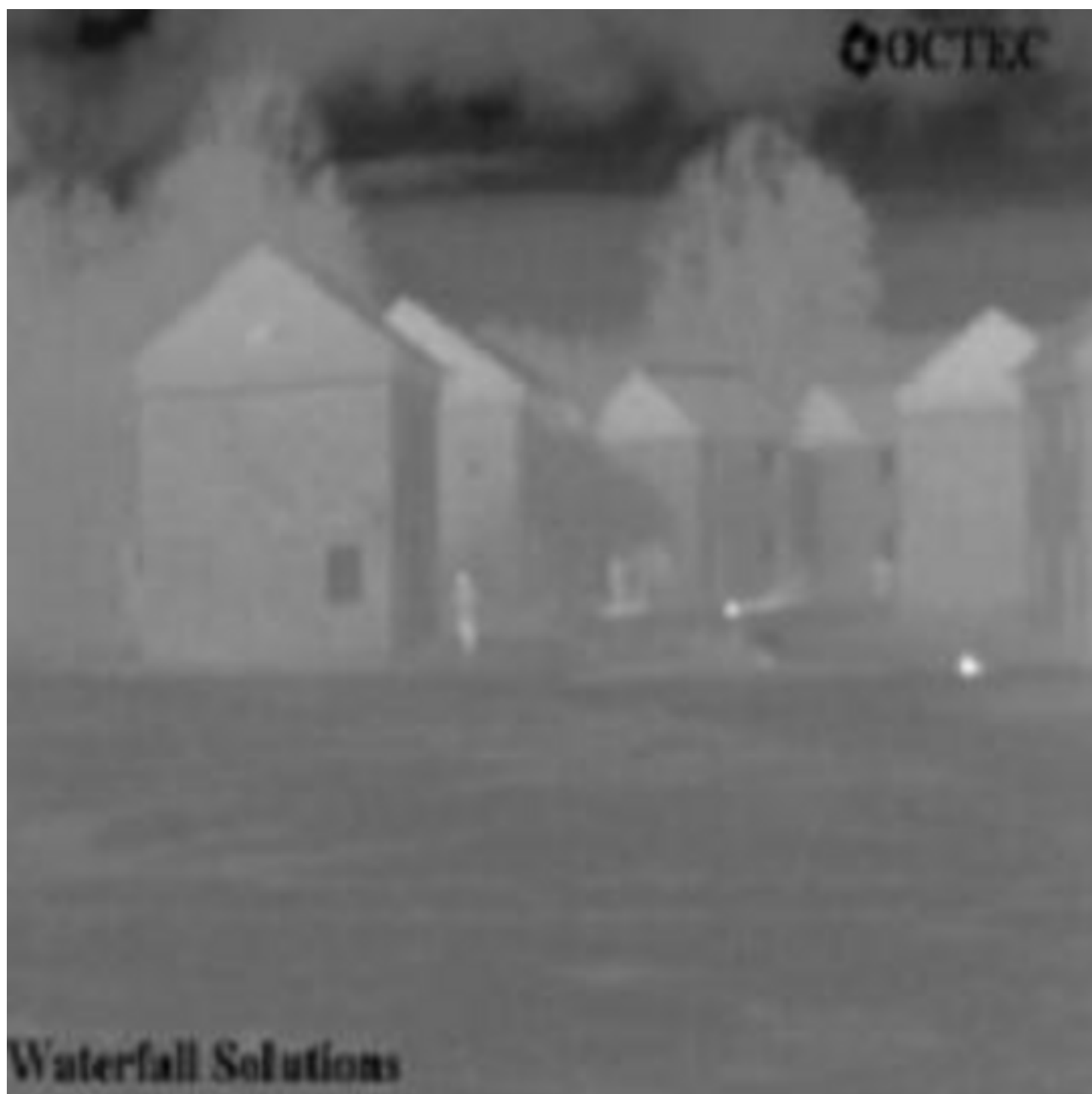










Table 1 Numerical results of Fig.3

Images	IE	AG	STD	Run time
Visual light color image	3.4236	2.856	27.1248	—
Infrared thermal image	4.6603	4.8559	32.8665	—
PCA-based fusion result	4.8325	5.9438	39.9533	0.2500
Wavelet-based fusion result	4.5077	6.0738	32.268	0.0940
CP-based fusion result	4.3297	6.7942	37.1387	0.0470
TLBO-CP fusion result	4.6996	9.9983	53.0902	11.6719

Table 2 Numerical results of Fig.4

Images	IE	AG	STD	Run time
Visual light color image	5.3444	17.8197	63.7882	—
Infrared thermal image	4.4731	6.5195	68.5229	—
PCA-based fusion result	5.1868	10.7996	62.9817	0.7960
Wavelet-based fusion result	5.2271	18.51	70.7156	0.3440
CP-based fusion result	5.1229	23.3201	81.2657	0.1570
TLBO-CP fusion result	4.4306	27.8164	95.9599	11.4069

Table 3 Numerical results of Fig.5

Images	IE	AG	STD	Run time
Visual light color image	4.9224	1.759	52.9171	—
Infrared thermal image	4.4127	1.7589	24.262	—
PCA-based fusion result	4.9454	1.7813	53.6764	0.0150
Wavelet-based fusion result	4.4394	2.3379	30.185	0.1090
CP-based fusion result	4.5823	2.6309	32.2092	0.1090
TLBO-CP fusion result	4.8984	2.725	48.7981	11.3909

Highlights

- . This paper presents an optimized method for visible and infrared images fusion employing TLBO method.
- . Fusion coefficients are non-linear adjusted adaptively by fitness function.
- . Proposed method outperforms other methods in both visual effect and objective evaluation.